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LiDAR system benchmarking for VRU detection in heavy goods vehicle blind spots

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***Abstract*—This article is related to using modern LiDARs and neural networks based algorithms for vulnerable road users (VRU) detection. The problem is obvious especially when considering blind spots of heavy goods vehicles. LiDARs have developed a lot recently and the results indicate that adults can be detected up-to 75 m distance from the sensor even thought that pattern recognition requires sufficient point cloud-resolution. Two different LiDAR brands have been compared to understand cost-benefits between LiDAR technologies. The results have been conducted using an automated passenger car while considering feasibility to big trucks. Due to automotive requirements, the processing rate is also considered since usually, the main bottleneck is computation power, which is limited in automotive products. The used neural network algorithm is Yolo based and has been designed for VRU detection.**

***Keywords*— 3D object detection, neural network, LiDAR, heavy goods vehicle, VRU, blind spot safety**

I. Introduction

A. Accidents involving pedestrians in Finland and in Europe overall

Whilst the number of pedestrians killed in road accidents has significantly reduced in the last 15 years, still 5320 pedestrians were killed in traffic accidents according to statistics from 2016 [1]. Number of fatalities varies by country, from 2,6 pedestrian fatalities per million population in Netherlands to Romania's 36,3 per million population. In the last three years in Finland, an average of 21 people have died and 360 pedestrians have been injured each year. Every tenth, and seven percent of all road deaths and injuries, were pedestrians. One in five victims died on the pedestrian crossings. Sixty percent of pedestrian injuries occurred on the pedestrian crossings [2]. Nearly half of all deaths and nearly a third of those injured were 65 years of age or older. Of the pedestrians who died on the pedestrian crossing, four out of five and almost one in three were injured were 65 years of age or older. This applies also to the whole of Europe also, where the elderly form the largest group in pedestrian fatalities, but the percentage of pedestrian fatalities is high for children as well. This is most likely attributed to their higher frailty and lower level of motorization.

During the darkest quarter of the year in Finland, half of all pedestrian injuries occurred in October-January. In particular, personal injuries on guardrails were concentrated in these months: 58 % of personal injuries on pedestrian crossings occurred during this period. In Europe the number increases during the autumn, peaks in December and then decreases in the spring, whereas the total number of fatalities increases during the spring and peaks in July.

The increase in pedestrian fatalities during the winter is probably caused by the higher risk for pedestrians in the darkness. The duration of darkness is longer than in other seasons and pedestrians are much less visible than vehicles, which can use lights. 45% of pedestrian fatalities in the EU occurred in darkness, whilst 39% of pedestrian fatalities were recorded in daylight. Pedestrian fatalities in darkness varies between countries, from 74% in Lithuania to 28% in Finland. The elderly form the largest group in pedestrian fatalities but the percentage of pedestrian fatalities is high for children as well. In Europe 50% off all pedestrian fatalities occurred between 4pm and midnight The highest percentage of pedestrians killed in road accidents was recorded on Fridays and Saturdays, while the lowest was recorded on Sundays.

B. Heavy goods vehicle pedestrian detection

Heavy vehicle detection requirements are radically different from the ones in passenger cars. Heavy goods vehicle driver has straight visibility only on the front side and partial visibility of both sides of the vehicle. All other recognition happens from mirrors. This causes danger for VRU when the heavy vehicle turns at an intersection. Usually the driver has a few blind spots around the vehicle. See Fig. 1. Traditional way to solve these problems is to make more mirrors but it's limited possibility because every extra mirror causes other blind spot behind it. Additionally, driver capacity to follow all

Fig. 1. Heavy goods vehicle with limited visibility for the driver.

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mirrors at urban traffic is limited. Dark time traffic is most difficult to solve with traditional mirrors or camera systems. A 25m long truck with a trailer doesn't give any light to its sides, so the driver cannot detect objects after they are out of the headlights range, camera systems are working with IR lights, but they require very powerful lights to be able to provide light to a 25m long area.

II. Related work

A. LiDAR sensors

Many popular LiDAR sensors are designed to use scanning techniques with mechanically spinning mirrors, which reflect laser beams to the environment as a horizontally rotating cone. The scanning resolution and the perception accuracy of these spindle-type LiDARs largely derives from their beam-count in the vertical direction. The beam-count of these LiDARs determines their perception capabilities, and is the limiting factor when perceiving an environment with mirror-rotating LiDARs. With this scanning technique, the horizontal resolution often outmatches the vertical resolution, which results in limited 3D information about the targets perceived by the LiDAR sensor. The information in vertical direction is increased with more scanning beams. However, the more precise hardware requirements for higher beam-counts also increase the cost of these mirror-rotating LiDARs, and they are more prone to physical damage from environmental stress factors due to the rotating mechanical parts.

Solid-state LiDAR systems have been developed as an alternative to the spinning LiDARs. Solid-state LiDARs attempt to minimize moving parts in the sensor, thus reducing their fragility. The goal of solid-state technology is to apply silicon chip technology to create less expensive and more robust LiDAR sensors with technologies such as micro-electromechanical systems (MEMS), optical phased arrays (OPA) and flash LiDAR [3]. Solid-state LiDARs can offer vertical resolutions similar to those of state-of-the-art rotating LiDARs with high beam counts. However, the problem is range since response from a single point is weak due to illuminating wide areas.

B. LiDAR object detection

With the development of LiDAR sensors and their increasing perception capabilities, point cloud data can be used in increasingly challenging applications such as object detection. Point cloud data from the environment can be processed to detect surrounding objects of interest. This can be applied to many fields of research, including autonomous driving. The perk of using point cloud data in object detection is the obtaining of 3D spatial information about surrounding objects, which allows the examination of an objects size, shape and movement. This information becomes more reliable and accurate when using higher resolution LiDARs.

Point cloud object detection can be performed in several ways. Pattern and feature recognition methods are a popular solution, and deep learning methods for 3D point clouds have gained great popularity in recent years. With modern LiDAR sensors however, the amounts of data that needs to be processed by computers is rapidly increasing. Deep learning solutions for point clouds are often computationally heavy, and therefore provide challenges when considering automotive applications. The processing times of automotive sensing systems should achieve real-time rates to fulfill safety requirements.

Sensor data fusion is a common method of processing different data types from differing sensors, and combining their data to yield information, which could not be obtained from a single sensor type alone. For example a LiDAR sensor provides accurate 3D spatial data about the environment, but it does not provide data such as the colors and other visual information of the surroundings. The visual features of the environment can be accurately perceived by a camera sensor, for example. As stated earlier, a major challenge of real-time point cloud processing is the amount of data available. Through sensor fusion, this data can be filtered in ways, which allow focusing on only the desired sub-sections of the point cloud i.e. interesting objects surrounding a vehicle. This provides the full benefits of the 3D point data, while greatly optimizing computation costs, when sensor data fusion is utilized to ignore unimportant parts of the point cloud. Such a method of data fusion is presented in [4]. The method is based on accurate inter-sensor calibration of a LiDAR and a camera, as it uses the output detection boxes mapped on an image by a 2D object detector, to form the initial search area in the lidar point cloud through 3D to 2D point projections. The clustering is then applied in the LiDAR point cloud with distance-based searching to form individual 3D clusters of the objects. In this method, the importance of the LiDAR resolution is apparent, as the algorithm relies on the 3D points reflected from the perceived object. A low-resolution LiDAR-sensor provides more uncertain 3D data about surrounding objects, while a higher resolution sensor provides more accurate and descriptive data about the object, allowing more reliable estimation of object properties.

III. Test setup

The tests were setup in a way that allows the comparison of the perception capabilities of two LiDAR sensors in an outdoors environment using the 3D object detection method of [4]. The algorithm was modified, however, to use Euclidean distance-based clustering to determine the final object 3D points based on the initial search areas provided by the 2D object detector. The goal of the testing was to perform identical measurements of the 3D detection of pedestrians in varying distances for both LiDAR sensors. The detection system was integrated on the VTT research vehicle Marilyn, which was equipped with the two LiDAR sensors used in this comparison, see Fig 2.

Fig. 2. VTT automated driving reseach vehicle 'Marilyn'.

A. Measurement system overview

The VTT test vehicle Marilyn was used as the platform for this measurement. The object detection algorithm of [4] was implemented on the vehicle with three sensor data processing computers, each with their own task. The data transfer between the computers was handled using an OpenDDS network [5]. An Nvidia Jetson Xavier NX deep learning

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device was used as a platform to run the vanilla YOLOv4 2D object detector trained on the COCO dataset [6]. The detector was using an input size of 512x512, which has the reported Average Percision (AP) of 43.0 %. The object detector processed images obtained from a Basler Ace color camera, and published the detection information through OpenDDS. The LiDAR data was processed by a Cincoze computer, which modified the LiDAR sensor raw data to a point cloud, and published it to the OpenDDS network. The data fusion and the measurements for the sensor comparison were performed on a Jetson Xavier AGX embedded device. The Xavier NX device was able to process data at a rate of about 8 Hz, and the LiDARs were set to output point clouds at 10 Hz. The Xavier AGX device performing the data fusion was set to process the incoming camera and LiDAR data as qucikly as possible, which resulted in a slightly uneven rate for the data fusion inference due to the different processing rates of the camera and LiDAR computers. Therefore, the measurements for the LiDAR comparison were calculated per frame, ignoring elapsed time in the measurements. The LiDARS used in the comparison were the Ouster OS1-32 sensor, and the Luminar Hydra 3 sensor. The measurements were collected by first performing individual measurements for the Ouster sensor, and then the same measurements were repeated using the Luminar sensor. The measurement system is presented in Fig. 3.

B. Pedestrian detection measurement setup

The goal was to perform measurements for both LiDARs in identical scenarios, for equal amounts of processed frames in a single scenario. The measurements were conducted in two separate sets. One for Ouster and one for Luminar. The measuring vehicle stood still for all measurements, with the pedestrian being the only moving target in front of the vehicle. Each set included four measurements. Three of those measurements were conducted with a pedestrian walking around in the critical distances shown in Fig 4. The fourth measurement was a scenario where the pedestrian is approaching from a large distance, walking towards the observing vehicle. For the critical distances, markings were drawn on the ground at the distances of 11.5, 18 and 25.15 meters.

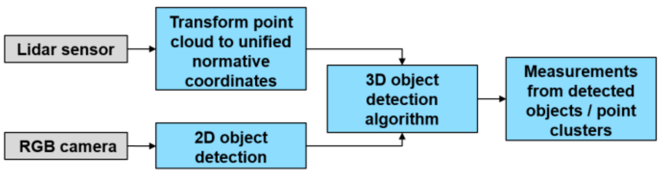

Fig. 3. Measurement system setup.

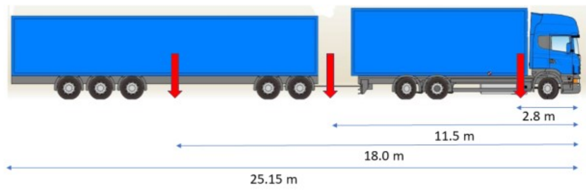

Fig. 4. Dangerous locations on a heavy goods vehicle where the risk of a pedestrian being run over is exceptionally great.

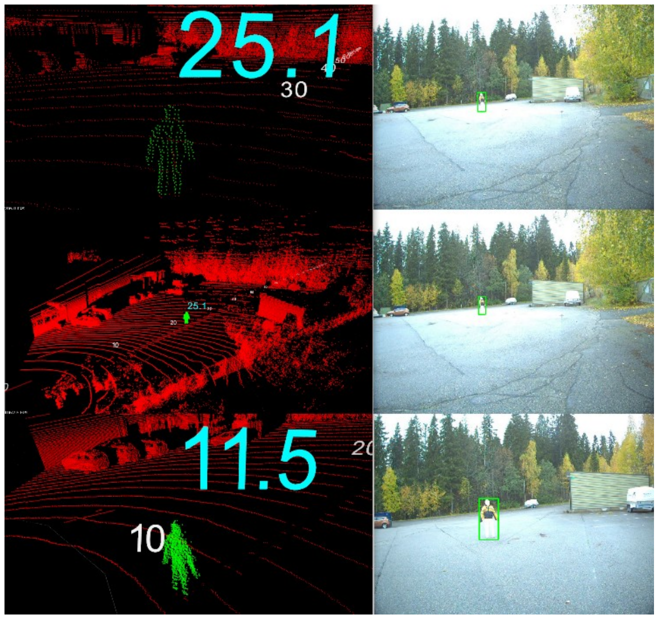

Fig. 5. Example of the object detection algorithm using the 2D detecttion boxes to form a point cluster representing the pedestrian. Luminar Hydra 3 is used here.

These distances were selected based on three particularly dangerous areas around the vehicle, where surprising sideways movement of the vehicles body while turning for example, can be a risk to the VRU, see Fig. 4. For each of these distances, a test subject walked back and forth in a line at a constant distance, and the measurement data was captured. These three measurements were conducted to provide some reference on the perception capabilities of the two LiDARs on heavy goods vehicle safety applications.

For the fourth measurement, the test subject was observed approaching the vehicle from a large distance. The measurement data stored from the target pedestrian included *xyz*-coordinates, distance, whether the pedestrian was succesfully extracted from the point cloud, and cluster-size of the extracted pedestrian object.

On some occasions, the point cloud extraction of the pedestrian object fails in situations where the 2D object detector locates the target from the image, but the LiDAR sensor cannot associate any 3D points to it i.e. the LiDAR has received no reflections from the target. Admittedly, this only occurred when measuring with the Ouster sensor. The cluster size refers to the final amount of LiDAR-points associated to the object after the detection algorithm is finished. This is the main measurement in assessing the reliability and perception capability of the LiDAR sensors in this research. An example of a pedestrian detection is shown in Fig. 5.

IV. Experimental Results

The measurements were completed for the critical distances of 11.5, 18.0 and 25.15 meters. The amount of frames measured varied slightly for the scenarios, as the measurement was controlled by hand. The frame amounts varied from 234 to 272. The observed point cluster data was analyzed by finding the minimum, maximum and mean cluster size for each of the measurement scenarios.

TABLE I. OUSTER OS1-32 PEDESTRIAN PERCEPTION

Ouster				
Distance (m)	11.5	18.0	25.15	Approach
Min. cluster size	60	23	10	1
Max. cluster size	98	45	22	626
Mean cluster size	73.4	31.4	15.5	69.7
Frame amount	259	243	272	193

TABLE II. LUMINAR HYDRA 3 PEDESTRIAN PERCEPTION

Luminar				
Distance (m)	11.5	18.0	25.15	Approach
Min. cluster size	409	207	127	36
Max. cluster size	942	507	339	2212
Mean cluster size	525.9	298.2	195.2	318.7
Frame amount	234	244	261	312

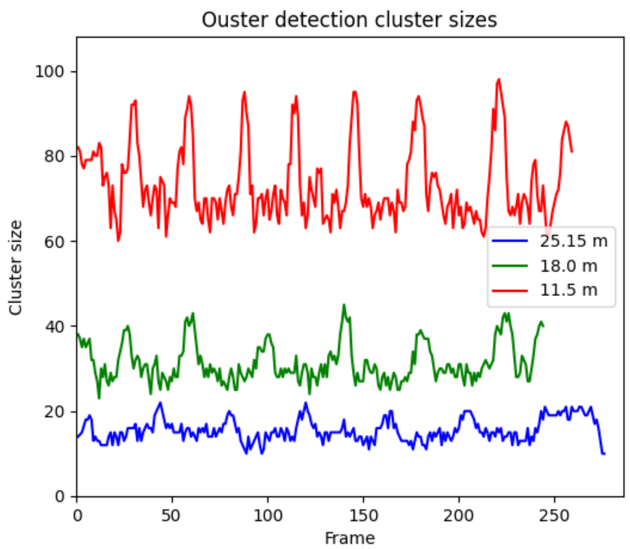

Fig. 6. Point-cluster sizes of the detected pedestrian on different distances for the Ouster OS1-32 LiDAR.

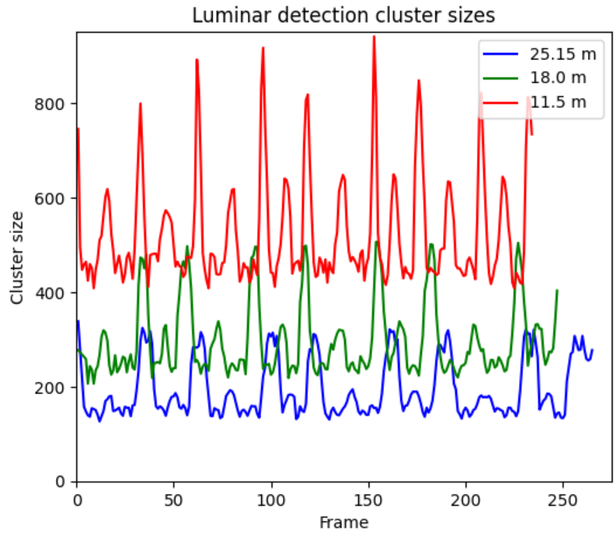

Fig. 7. Point- cluster sizes of the detected pedestrian on different distances for the Luminar Hydra 3 LiDAR.

Tables I and II, and Fig. 6 and Fig. 7 show the numbers of points reflected from the pedestrian target for both of the LiDAR sensors. The 'Approach' column refers to the scenario, where the pedestrian target is approaching directly towards the measuring vehicle at a regular walking speed. The cluster size has regular increases in point amounts, this is caused by the changes in the target pedestrians direction of movement. While turning, the pedestrian faces the camera and the LiDAR, which results in larger visible surface, and therefore more LiDAR points are reflected from the target. This is seen on all of the scenarios where the pedestrian is

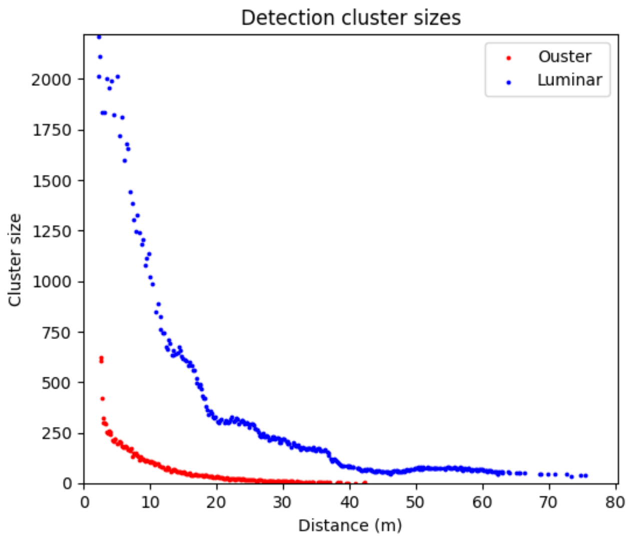

Fig. 8. Point-cluster sizes of the detected approaching pedestrian for both LiDAR-sensors.

pacing back and forth at a certain distance. The measurement only included situations where a succesful pedestrian detection occurred. Therefore, the Frame amount of Tables I and II is very different for the 'Approach' measurement, as the Luminar sensor was able to see the pedestrian from greater distances than the Ouster sensor.

Fig. 8 shows the relation between the measured distance of the object and the objects point cluster size. The idea is to imitate a situation where the sensors are installed on the front bumper or the sides of a large truck. The pedestrians distance from the vehicle was estimated by calculating the center of mass of the point cloud points representing the pedestrian. Figure 5 also gives insight on the perception distance of YOLOv4. For the Luminar sensor, the detections stabilize at a distance of over 60 meters, which is when the YOLOv4 detector begins to provide continuous detections of the pedestrian. The Ouster sensor does not receive reflections from the pedestrian at this distance, however, and starts perceiving the pedestrian at distances of over 40 meters.

The difference between the amounts of reflected points is significant. For the distance of 11.5 meters, the Luminar returned approximately 7.2 times more points than the Ouster on average. At 18 meters, the Luminar returned 9.5 times more points on average, and at 25.15 meters, 12.6 times more points on average. Both of the sensors managed to continuously detect the pedestrian at all of the critical distances.

V. Conclusions and future work

The measurements provided insight on the perception capabilities of a lower-resolution spindle-LiDAR, and a state-of-the-art solid-state LiDAR. The tests were conducted in a way which examined both sensors applicability in a heavy vehicle safety system for detecting pedestrians moving in dangerous proximities and critical risk areas of a heavy goods vehicle. The greater point amounts of the Luminar allow more reliable postprocessing operations. Examples of this are object tracking, and size estimation.

Compared to previous studies with 3D-camera systems in heavy goods vehicles, the LiDAR approach allows more reliable detection along the full length of the vehicle [7]. The results show the current advancement and potential of state-of-the-art solid-state LiDARs compared to the popular lower-resolution spindle-LiDARs. The Luminar Hydra 3 sensor was able to associate about 40 3D points to the pedestrian target from distances as large as 75 meters. For reference, the Ouster 32 beam sensor associated about 31.4 points on average to the pedestrian from an approximate distance of 18 meters. The prowess of modern state-of-the-art LiDARs provides increasing possibilities in critical safety applications such as heavy vehicle urban driving, where accurate tracking and classification of other road users is critical. However, the mounting position has influence to the field of view. Usually, the LiDARs in a truck are installed either on the roof or front bumper where distance to ground does not degrade resolution in proximity.

In the future, these types of test setups could be integrated into actual heavy vehicles, to obtain practical results about the usability of LiDAR-based object detection systems for pedestrian detection in blind spots. This research used a passenger vehicle for mounting the measurement sensors, so performing these types of measurements with sensors installed on an actual heavy goods vehicle would provide further information on the subject. The setup of this research utilized an RGB camera, whose image stream was processed by a neural network to support the LiDAR sensor. In the future, the RGB camera could be replaced with an IR system for detection support. Thanks to the high-resolution point clouds provided by the Luminar Hydra 3 and other state-of-the-art sensors, VRU detection could also be performed by purely point cloud analyzing algorithms more reliably than before.

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References

[1] European Road Safety Observatory, Traffic Safety Basic Facts 2018 - Pedestrians, 2018

[2] Finnish Road Safety Council, Statistics report on pedestrian road accidents, May 2021

[3] A. K. Aijazi, L. Malaterre, L. Trassoudaine, P. Checchin, Systematic evaluation and characterization of 3D solid state lidar sensors for autonomous ground vehicles, August 2020

[4] T. Miekkala, 3D object detection using lidar point clouds and 2D image object detection, May 2021

[5] OpenDDS, “OpenDDS”, 2021, Available: https://opendds.org/about/

[6] A. Bochkovskiy, C. Y. Wang, H. Y. M. Liao, YOLOv4: Optimal Speed and Accuracy of Object Detection, April 2020

[7] P. Pyykönen, A. Virtanen, A. Kyytinen, 2015 IEEE International Conference on Intelligent Computer Communication and Processing (ICCP): Optimal Developing intelligent Blind Spot Detection system for Heavy Goods Vehicles, Spetember 2015